Emergent complexity: what uphill analysis or downhill invention can not do ⋆

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Abstract

In these notes we review emergent phenomena in complex systems, emphasizing ways to identify potential underlying universal mechanisms that generates complexity. The discussion is centered around the emergence of collective behavior in dynamical systems when they are poised near a critical point of a phase transition, either by tuning or by self-organization. We then argue the rationale for our proposal that the brain is naturally poised near criticality reviewing recent results as well as the implications of this view of the functioning brain.

Key words: brain, phase transitions,, critical phenomena, complex networks

1 Uphill analysis and downhill invention

Decades ago, the paradigmatic Braitenberg's thought experiments in "Vehicles, experiments in synthetic psychology" [1] already showed that "vehicles" with even rudimentary internal structure can behave in surprisingly complex ways. He was able to demonstrate that by wiring the vehicle few motors and sensors in different ways it can generate behaviors we might call hate, aggression, love, foresight, or even optimism. In his own words:

> "It is pleasurable and easy to create little machines that do certain tricks. It is also quite easy to observe the full repertoire of behavior of these machines – even it it goes beyond what we had originally planned, as it often does. But it is much more difficult to start from the outside and try to guess internal structure just form the observation of the data. [...] Analysis is more difficult than invention in the

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> sense in which, generally, induction takes more time to perform than deduction: in induction one has to search for the way, whereas in deduction one follows a straightforward path. A psychological consequence of this is the following: when we analyze a mechanism, we tend to overestimate its complexity."

Braitenberg was successful conveying the idea of a "law of uphill analysis and downhill invention" capturing the difficulty of guessing the internal structure from the observation of behavior compared with the easiness of building artifacts exhibiting the behavior.

Recent work on complex systems allows for rather similar, albeit far reaching, suggestions. It is now understood how robust behaviors can emerge in large nonlinear dynamical systems given some minimal conditions. In some cases these behaviors -or attractors, in the jargon- are universal (e.g, can be equally seen in disparate domains) not only qualitatively but also in their quantitative expressions. The intention of these notes is to link these results with the problem of understanding brain function. It shares Braitenberg's motivation, without restricting our view of the brain to low dimensional systems (i.e., two motors, two sensors, and a few "neurons"). Besides its realism, the high dimensionality assumption is preventing us from "inventing" any structure, which then must emerge only from self-organizing dynamics. The emphasis is to see what kind of behavior can these dynamical systems generate, under which constraints, etc. Much in the same way that the vehicles exhibited love, hate and so on, we investigate the generic properties of this scenario identifying those relevant to the problem of brain function.

The paper is organized as follows: Section 2 illustrates the idea of emergence in complex systems,by describing previous work on the dynamics of social insects. Section 3 discusses what is considered as complex followed by an account of the main theoretical efforts explaining natural complexity as a result of being poised at a state of affairs close to criticality. Section 4 discusses how to get around Braitenberg's law, and which aspects of brain dynamics might benefit from this viewpoint. The final comments are dedicated to review the arguments and recent results as well as the implications of this view of the functioning brain.

2 Emergence

Emergence refers to the unexpected spatiotemporal patterns exhibited by complex systems. As discussed at length elsewhere [2,3,4], complex systems are usually *large* conglomerate of *interacting* individuals, each one exhibiting some sort of *nonlinear* dynamics. In addition, there is usually energy being pumped into the system, thus some sort of driving is present. The three *emphasized* components are necessary (although not sufficient) conditions for a system to exhibit at some point emergent behavior. Suppose that the elements are humans, who are driven by food,

sun light and other energy sources, they can form families and communities. At a certain point in their evolution, they give themselves some political structure, with, say, chiefs and counsellors. Whatever the type of structure that emerge it is unlikely to appear if one of the above emphasized elements is absent. It is well established that a small number of isolated linear elements is not going to produce much unexpected behavior (mathematically, this is the case in which everything can be formally anticipated). We will consider the dynamic of swarms, as a specific example

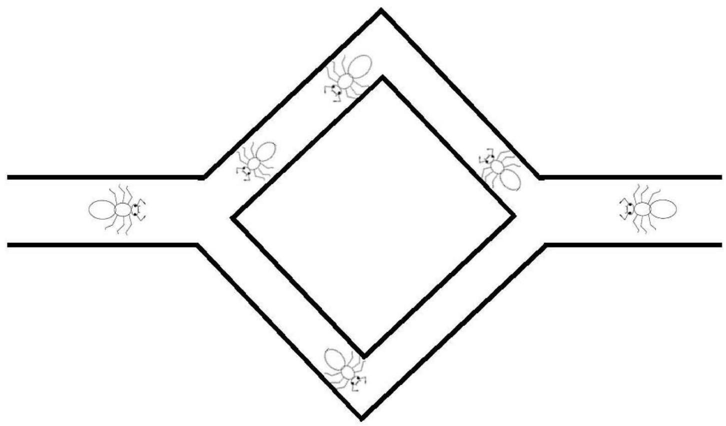

Fig. 1. In the binary bridge experiments ants are exposed to bridges connecting two or more areas. Eventually they discover and cross the bridges.

with the three necessary components which will help make the point clear. Social insects represent the paradigm of cooperative dynamics [5]. In the case of foraging ants they interact to organize trails connecting the nest with the food sources, forming structures with sizes that usually are several order of magnitude larger than any of the individual's temporal or spacial scales. Therefore, the relevant problem here is to understand the microscopic mechanism by which relatively unsophisticated ants, can build and maintain these very large macroscopic structures. [1]

To study this problem, Millonas introduced [8] a spatially extended model of what he termed "protoswarm". In the swarm, there are two variables of interest, the organisms (in large number) and a field, representing the spacial concentration of a scent (such as pheromone). As in real ants, the model's organisms are influenced in their actions by the scent field and in turn they are able to modify by depositing a small amount of scent in each step. The scent is slowly evaporating as well. The organisms only interact trough the scent's field. The model is inspired in the behavior of real ants, in which they are exposed to bridges connecting two or more areas where the ants move, feed, explore, etc. Eventually they will discover and cross one of the bridges. As it is illustrated in Figure 1 they will come to a junctions where they have to choose again a new branch, and continue moving. Since ants both lay

[1] We touch here only the surface of this problem, the interested reader will find the full account in [6,7,8,9,10] as well as the most recent extension of this work to image processing [11] as well as to some fascinating non human art [12].

and follow scent as they walk, the flow of ants on the bridges typically changes as time passes. In the example illustrated in Figure 1, after a while most of the traffic will eventually concentrate on one of the two branches. The collective switch to one branch is the emergent behavior, something that can be understood intuitively on the basis of the positive feedback between scent following, traffic, and scent laying. Numerous mathematical models and computer simulations were able to capture this behavior observed in the laboratory as well [13,14,15]. The under-

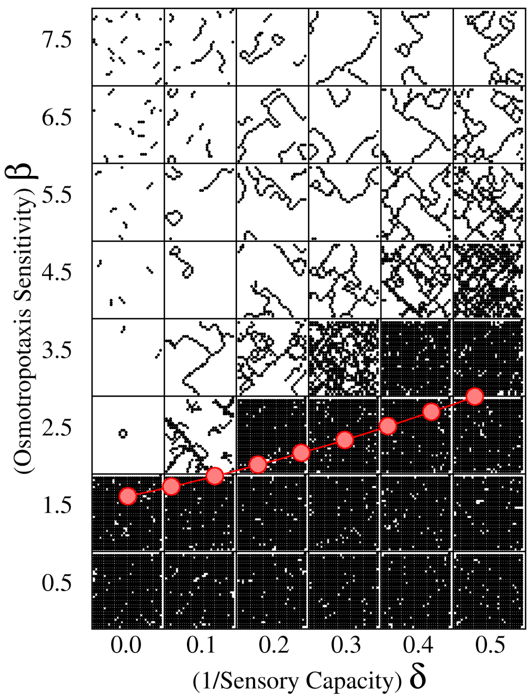

Fig. 2. Emergent patterns exhibited by synthetic swarms with different values of gain (β) and dynamic range (δ) in the ants' sensory system. For each parameter β and δ value indicated on the axis, the dots in each of the 48 squares is a snapshot of the ants' positions at the last ten iterations after 5000 time steps starting from a random initial distribution of agents. The circles joined by a line are the predicted values for the phase transition. There are three distinct behaviors: one region (below the line) where behavior is random, a second (above the line) where line of ordered traffic appears, and yet another with clustered immobile ants (far above the line). (32x32 lattice, other parameters as in [6,7].)

standing gained with the bridge experiments can be extended to more sophisticated settings, such as freely exploring organisms. The insight comes from a rather clever way that Millonas's model discretized space. For descriptive purposes, the model can be considered as a network constructed by connecting each point of a square lattice to its eight nearest neighbors with the bridges of Figure 1. Thus, at each step (literally) each ant makes a decision to choose one of eight bridges; and deposits a fixed amount of pheromone as it walks, that is all. The decision is based on the scent amount at each of the eight locations. The ants' sensory apparatus embedded in a physiological response function, was modelled following biological realism, hav-

ing two parameters, one which could be considered analogous to gain and the other the inverse of sensory capacity (or dynamic range). The plot in Figure 2 condenses the results from the numerical simulations with different values for the physiological response function. At each combination of the explored β and δ values there is a square plot which depicts the locations of each ant at the last ten steps of the simulation. It can be seen that ants converge to different behaviors depending on the parameter' values. For values of both small gain and small dynamic range ants execute a random path, resulting in the plots fully covered, as in the right bottom corner. That makes sense, because of the low sensitivity ants are just making random choices at each juncture. For large enough gain (top left corner), ants senses saturate resulting in clusters of immobile ants in the same attracting spot. It is in between these two states, one disordered and the other frozen, that the swarm can organize and maintain large structures of traffic flow as those seen in nature. The

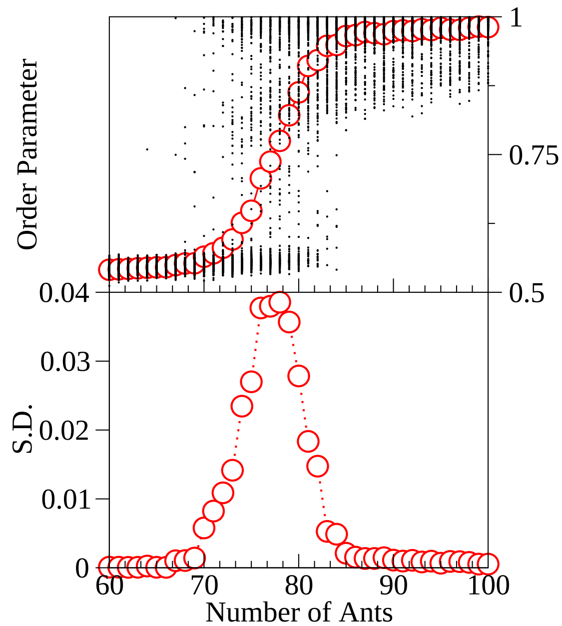

Fig. 3. Collective swarm behavior near the phase transition. Collective order (top) increases as a function of increasing density of ants and fluctuations magnitude (bottom) diverges at the critical point. (Order parameter values from individual runs are plotted using dots and circles for the average. S.D: Standard deviation of the data in the top panel.)

stability analysis in the theory in [8] makes straightforward to understand the transition between the disordered walks and the complex structures of trails (line and circles in Fig. 2). Intuition already suggests that the model's β,δ values at which the order-disorder transition happens must depend on the number of ants able to reinforce the scent field. In Figure 3 results from several hundreds runs with fixed parameters ($\beta = 3.5, \delta = 0.1$) and increasing density of ants are shown. The degree of collective order was evaluated by the proportion of ants "walking" on lattice

points having above average scent concentration (see further details in [6,7]). The top panel shows a plot of the results where the dots indicate the outcome of each individual run (with different initial conditions) and circles the average of all runs. For low ants' density the expected random behavior is observed, with equal likelihood for ants to be in or out of a high scent field. For increasing number of ants the swarm starts to order to reach the point in which the majority of the ants are walking on a field with scent concentration larger than the average. Of note is the generic increase of the amplitude of the fluctuations right at the transition, as it is shown in the bottom panel of Figure 3.

These results were the first to show the simplest (local, memoryless, homogeneous and isotropic) model which leads to trail forming, where the formation of trails and networks of ant traffic is not imposed by any special boundary conditions, lattice topology, or additional behavioral rules. The required behavioral elements are stochastic, nonlinear response of an ant to the scent, and a directional bias. There are other relevant properties, discussed in detail elsewhere [6,7], that arise *only* at the region of ordered line of traffic, including the ability to reconstitute trails and amplify weak traces of scent. The main conclusion to be drawn from the work commented here is that scent-following is sufficient to produce the emergence of complex patterns of organized flow of social insect traffic all by itself (and not just sufficient to allow for trail following behavior). Lets recall now the three aspects emphasized at the beginning of this section as crucial for emergence. As shown in Fig. 3 a certain minimum density of ants is needed since trails need to be reinforced, the response to the scent need to be nonlinear, and ants must interact (through the field). These are all essential ingredients for the emergence of these complex patterns of swarming behavior.

3 What is complex?

We have seen in the previous section that complex structures of trails emerge near a phase transition. But, what it means for something to be complex? Except for man-made objects, complexity *is* what we see usually all around us. Instead of *ad hoc* definitions, it is much more telling to discuss how nature manages to build the complexity we are all embedded in. As the opening sentence of Per Bak [2] book reminds us:

> *"How can the universe start with a few types of elementary particles at the big bang, and end up with life, history, economics, and literature. The question is* ***screaming out to be answered*** *but it is seldom even asked. Why did the big bang not form a simple gas of particles or condense into one big crystal? We see complex phenomena around us so often that we take for granted without looking for further explanation. In fact, until recently very little scientific effort was devoted to understanding why nature is complex?"*

The additional appeal of *explaining* complexity is that entails *figuring out* mechanisms, nothing essentially different from the long prolific tradition of physics in other more simple systems. That work provided us with all the laws needed to understand a large body of problems. But that is history, the problem scientists are faced with now is to write down the equations able to produce the surrounding complexity one sees. Clouds, epidemics, rainy as well as drought seasons, flowers, storms, earthquakes, economics, diversification and extinction of biological species, galaxies, societies, wars and peace are a few examples of complex systems we need laws for. Some, will argue as nonsensical to even treat economics within the realm of physics, others that it is perfectly possible, and furthermore that it won't be necessary to conceive as many laws as objects of interest. After all, they consider, Newton's laws are unique; there is not one written for falling apples, another one for falling airplanes, etc. Work in recent years shows that there are large classes of complex systems obeying the same universal laws, making simpler the task of figuring out how they work. Nowadays, this concept is more than intuition and there are concrete examples in which this universality have already been demonstrated [2,16,17].

4 Emergent complexity is always critical

Look around and observe what you see. It is fair to say that, for the most part, the objects and phenomenology we do understand have a common feature: their regularity and uniformity. In contrast, nature is by far *non homogeneous, or non uniform*. This observation can not be brushed off for trivial or exceptional, it is the rule and as Bak argued [2] a question screaming out to be answered. Attempts to explain and generate this kind of non uniformity included many mathematical models and recipes, but few succeeding in creating complexity without embedding the equations with it. The point being that including the complexity in the model will only be a simulation of the real system. That is not what we are after. We want rather to understand complexity which implies to discover the conditions in which something complex emerges from the interaction of the constituting non-complex elements. Initial inspiration about the possible origins of natural complexity was provided by work in the field of phase transitions and critical phenomena. To expand on these ideas lets recall the scenario of ferromagnetic-paramagnetic phase transition illustrated in Figure 4. A material is said to be ferromagnetic if it displays a spontaneous magnetization in absence of any external magnetic field. If, for instance, we heat up an iron magnet the magnetization gets smaller and finally reaches zero, following the curve depicted in the figure. If one could see the orientations of the individual spins, will realize that at low temperature the system is very ordered with many very large domains of equally oriented spins, a state that is practically invariant in time. On the other extreme, at very high temperatures, spins' orientation changes constantly, they are correlated at only very short distances and

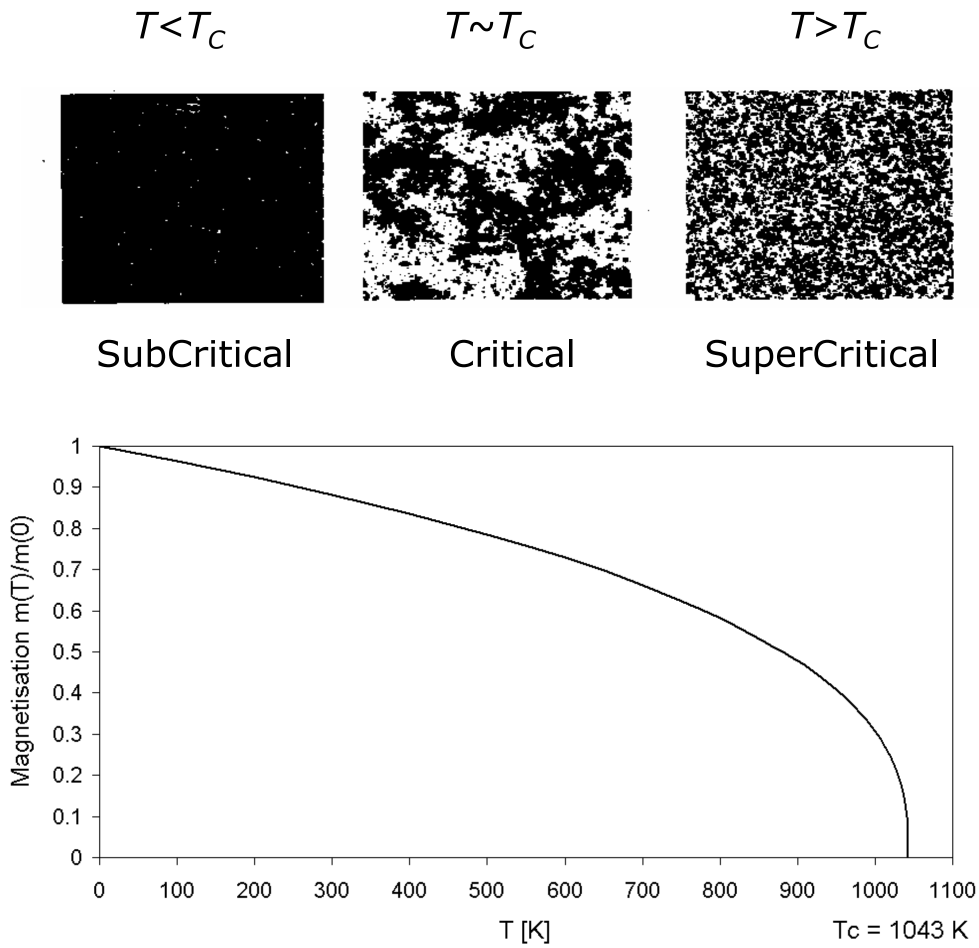

Fig. 4. Complex is critical: Example of a ferromagnetic-paramagnetic phase transition. Bottom: Temperature dependence of magnetization m(T) for Fe. Top three panels are snapshots of the spins configuration at one moment in time for three temperatures: subcritical, critical and supercritical from numerical simulations of the Ising model (d=2). Notice that both sub- and supercritical conditions result in homogeneous states, while at the critical temperature the system exhibits highly inhomogenous correlated domains. This is typical for any system exhibiting a second order phase transition.

as a consequence the mean magnetization. which expresses the collective behavior, vanishes; hence, the iron is not a magnet anymore. In between these two homogeneous states, at what is called the critical temperature T_c, the system exhibits very peculiar fluctuations both in time and space. For example, the magnetization temporal fluctuations are known to be scale invariant. Similarly, the spatial distribution of spins' clusters show long range (power law) correlations. At the critical point, these large dynamic structures emerge, even though there are only *short-range* interactions between the systems' elements. Thus, at the critical temperature, the system exhibits a greatly correlated (up to the size of the system) state which at the same

time is able to fluctuate wildly in time at all scales.

One would agree that, at least qualitatively, the spatiotemporal patterns observed at the critical point resemble natural objects (say clouds or coastlines), an impression that could be reinforced by further quantitative analysis of their self similarity both in time and space. This is also consistent with the results in section 2 confirming that complex patterns of ants' traffic emerge only near the critical line. However, given the fact that these properties are present *only at* the critical point, criticality can not be suggested as a source of complexity, unless a robust mechanism to tune nature towards criticality is provided.

That was precisely Per Bak's contribution [2] with the theory of Self Organized Criticality (SOC) [2]: to identify the probable mechanisms by which large dynamical systems can drive themselves towards a critical point. The theory's -already two decades old- main claim is that large non linear dynamical systems can have an intrinsic tendency to evolve spontaneously toward a critical state characterized by spatial and temporal self-similarity, of the kind seen to abound in nature. The crucial assumption in all SOC models is the interaction of many nonlinear elements and the slow pumping of energy. In the original formulation, the basic idea behind SOC was framed in a toy model, e.g., a *thought* experiment, using a mathematical model of a sand pile, inspired in the dynamics of avalanches seen in real piles of sand. To visualize the concept, think of building a real sand pile. By dropping sand slowly, grain by grain on a surface, eventually one reaches a situation in which the slope of the pile is not growing anymore. At this point the pile is critical, i.e. it has a slope at which any further addition of sand will produce sliding of sand (avalanches). This sliding can at times be very small or at some others can cover the entire size of the system. One quickly realizes, that each avalanche mobilizes only enough sand to decrease the local slope below the critical value. In that way the system *tunes itself* to a point by dissipating just enough energy (in the avalanches) to become barely subcritical, while the slow but continuous pumping of energy assures the return towards criticality. This self organized critical state is characterized by scale-invariant distributions for the size and the lifetime of the avalanches.

Considering the problem at hand, one would imagine that the SOC model needs to be very elaborate, but that it is not the case. The 2D version of the model runs on a square grid. Each site is identified by a position x and y and its state solely characterized by a local "slope" $z(x,y)$. Starting with a flat surface $z(x,y) = 0$, at each step one chooses an arbitrary location and drops a grain of sand, causing $z(x,y) = z(x,y) + 1$. Anytime that z, at any location, is larger than a threshold of 4, the z value at that location is decreased by 4 and the four neighbors z's increased by 1, these are the avalanches. That is all!.

It is important to reflect for a minute on the properties of the self-organized critical state. First of all, the behavior one observes in the sand pile experiment is highly non-uniform; that is, most of the times nothing happens, infrequently big

avalanches occur, but also everything in between is possible with a probability inverse to the slides sizes. In addition, the non-uniformity happens for the same input, a single grain of sand. However unpredictable this could sound it is not random behavior, since it is observed in a completely deterministic model. The reason for the seemingly unpredictable dynamics lies in the high dimensionality of the system. When we add a single grain, the future of the pile is written in the precise state of each of the other millions of grains. This -only apparent- unpredictability is different from the dynamics of deterministic chaos, which is also erratic behavior but produced by *low dimensional* deterministic systems. Among other contrasting properties, one should note that sand piles (and SOC in general) have a long memory, in the sense that the pile is shaped by the previous history of events (avalanches) while in deterministic chaos the system forgets exponentially its past. The long memory have a spatial counterpart discussed in the context of magnetization above. Of note is that the critical state is the most *unstable* and at the same time the most *robust* attractor for the dynamics. The most unstable, because a single grain of sand have the potential of producing an avalanche of the entire sand pile. The most robust, because the system will eventually come back to the same unstable state. The simultaneous presence of both instability and robustness properties is an important peculiarity of SOC systems, not seen in any other dynamical system. It is clear that the system is self-organized, and it is hard to identify where in the model (or in the real pile) is predicted the emergence of these peculiar properties.

For the last two decades SOC has been studied well beyond the initial sandpile metaphor, in models and experiments, in a wide diversity of disciplines from biology to economics, from astrophysics to linguistic, shedding light over the mechanisms generating complexity (for recent reviews see [3,18]). Thanks to this work, it is now well established that a large class of driven nonlinear dynamical systems can evolve to a critical state in which the above discussed non uniformity will spontaneously appear. The only necessary condiments are: 1) a large number of degrees of freedom, 2) each one must be non linear and 3) energy needs to be pumped to the system relatively slowly and will be dissipated as fractals in space and time. The common theme across these models and systems is the emergence of complexity at the critical state. [2]

5 A way out of Braitenberg's law dead end

Recall the introductory paragraph emphasizing the obstacle to explain behavior in terms of the underlying *collective*. In Braitenberg's words it is much easier to invent something that replicates the behavior than to figure out the mechanisms from its observation. But Braitenberg's downhill invention won't help much as soon as

[2] Note that similar observation was made in the swarm model of section 3, where complex structures of traffic form *only* at the vicinity of the critical phase transition.

one chooses to explain some more sophisticated cognitive behavior. At the same time, reductionist analysis is immediately precluded by the large size and the non-linearities of the system. Apparently it is a dead end. *The way out suggested here is to ask what kind of behavior large dynamical systems will universally exhibits.* In other words the strategy is to look at the fundamental laws for the collective of neurons, in the hope of finding a family of self-organized invents! We can certainly anticipate the most probable criticism: all we will be describing is the mind as an epiphenomena of the brain.

We can start the search guided by some relevant facts as source of inspiration. The brain have, as a collective, some notoriously conflictive demands. On one side it needs to be "integrated" while at the same time being able to remain "segregated", as discussed extensively by Tononi and colleagues [19,20,21]. This is a non trivial constraint, nevertheless mastered by the brain as it is illustrated with plenty of neurobiological phenomenology. Suffice to think in any conscious experience to immediately realize that it always comprises a single undecomposable integrated state [20]. This integration is such that once a cognitive event is committed, there is a refractory period (of about 150 msec.) in which nothing else can be thought of. At the same time the large number of conscious states that can be accessed over a short time interval exemplify very well the segregation property. As an analogy, the integration property we are referring to could be also interpreted as the capacity to act (and react) on an all-or-nothing mode, similar to an action potential or a travelling wave in a excitable system. The segregation property could be then visualized as the capacity to evoke equal or different all-or-nothing events using different elements of the system. This could be more than a metaphor.

While the study of this problem is getting increasing attention, the mechanisms by which this remarkable scenario can exist in the realms of brain physiology is not being discussed as much as it should. Recalling the properties of the dynamical scenario described in section 4, we propose that the integration-segregation capacity of the conscious brain is related to it being poised at the critical point of a phase transition. It is important to note that there is no other conceivable dynamical scenario or robust attractor known to exhibit these two properties simultaneously. Of course, any system could trivially achieve integration and long range correlations in space by increasing link's strength among faraway sites, but these strong bonds would prevent any segregated state. At the critical point these and others properties -equally crucial for brain function- appear naturally. If the concept is correct, statistical physics could help to move the current debate from phenomenology to understanding of the lower level brain mechanisms of cognition.

The brains we see today are here precisely because they got an edge to survive, in that sense how consistent is the view of the brain near a critical point with these Darwinian constraints? The brains are critical because the world in which they have to survive is up to some degree critical as well. In a sub-critical world everything would be simple and uniform (as in the left panel of Figure 4) and there would be

nothing to learn; a brain will be completely superfluous. On the other extreme, in a supercritical world everything would be changing all the time (as in the right panel of Figure 4); there, it would be impossible to learn. Brains are only necessary to navigate in a complex, critical world, where even the very infrequent events have still a finite opportunity to occur.[3] In other words we need a brain *because* the world is critical [2,3,22,23,24]. Furthermore, a brain not only have to remember, but also to forget and adapt. In a sub-critical brain' memories would be frozen. In a supercritical brain, patterns change all the time so that no long term memory would be possible. To be highly susceptible, the brain itself has to be in the in-between critical state.

A number of features, known to be exhibited by thermodynamic systems at the critical point, should be immediately observed in experiments, including:

(1) At large scale:
Cortical long range correlations in space and time.
Large scale anti-correlated cortical states.

(2) At smaller scale:
"Neuronal avalanches", as the normal homeostatic state for most neocortical circuits.
"Cortical-quakes" continuously shaping the large scale synaptic landscape providing "stability" to the cortex.

(3) At behavioral level:
All adaptive behavior should be "bursty" and apparently unstable, always at the "edge of failing".
Life-long learning should be critical due to the effect of continuously "raising the bar".

In addition one should be able to demonstrate that a brain behaving in a critical world performs optimally at some critical point, thus confirming the intuition that the problem can be better understood considering the environment in which brains evolved.

In the list above, the first item concerns the most elemental facts about critical phenomena: despite the well known *short range* connectivity of the cortical columns, *long range* structures appear and disappear continuously, analogous to the long ant's trails shown to form near the critical point in section 2. The presence of inhibition as well as excitation together with elementary stability constraints lead to conclude that the spatiotemporal cortical dynamics should exhibit large scale anti-correlated spatial patterns as well, as reported recently in [25]. The features at smaller scales could have been anticipated from theoretical considerations as well, but avalanches were first observed empirically in cortical cultures and slices by Plenz and colleagues [26]. According to a recent review [27] neuronal avalanches

[3] As the very big avalanches in the SOC model, discussed in section 4.

can be conceived as the atom of neuronal ensembles.

According to recent work, our senses seems to be operating at a critical point as well. To move around, to escape from predators, to choose a mate or to find food, the sensory apparatus is crucial for any animal survival. But it seems that senses are also critical in the thermodynamic sense of the world. Consider first the fact that the density distribution of the various forms of energy around us is clearly inhomogeneous, at any level of biological reality [4], from the sound loudness any animal have to adapt to, the amount of rain a vegetal have to take advantage. From the extreme darkness of a deep cave to the brightest flash of light there are several order of magnitude changes, nevertheless our sensory apparatus is able to inform the brain of such changes. It is well known that isolated neurons are unable to do that because of their limited dynamic range, which spans only a single order of magnitude. This is the oldest unsolved problem in the field of psychophysics, tackled very recently by Kinouchi and Copelli [28] by showing that the dynamics emerging from the *interaction of coupled excitable elements* is the key to solve the problem. Their results show that a network of excitable elements set precisely at the edge of a phase transition - or, at criticality - can be both, extremely sensitive to small perturbations and still able to detect large inputs without saturation. This is generic for any network regardless of the neurons' individual sophistication. The key aspect in the model is a local parameter that controls the amplification of any initial firing activity. Whenever the average amplification is very small activity dies out; the model is subcritical and not sensitive to small inputs. On the other hand, choosing an amplification very large one sets up the conditions for a supercritical reaction in which for any - even very small - inputs the entire network fires. It is only in between these two extremes that the networks have the largest dynamic range. Thus, amplification around unity, i.e., at criticality, seems to be the optimum condition for detecting large energy changes as an animal encounters in the real world [29]. It is only in a critical world that energy is dissipated as a fractal in space and time with the characteristic highly inhomogeneous fluctuations. Since the world around us appears to be critical, it seems that we, as evolving organisms embedded in it, have no better choice than to be the same.

At the next level the suggestion is that human (and animal [30]) behavior itself should show indications of criticality. Learning obviously must be considered candidate to be critical as well, if one realizes that for teaching any skill one chooses increasing challenge levels, which are easy enough to engage the pupils but difficult enough not to bores them. This "raising the bar" effect continues trough out life, pushing the learner continuously to the edge of failure! It would be interesting to measure some order parameter for sport performance to see if it shows some of these features for the most efficient teaching strategies.

[4] If one comfortably accept these facts then is left to believe that the world as a whole is critical.

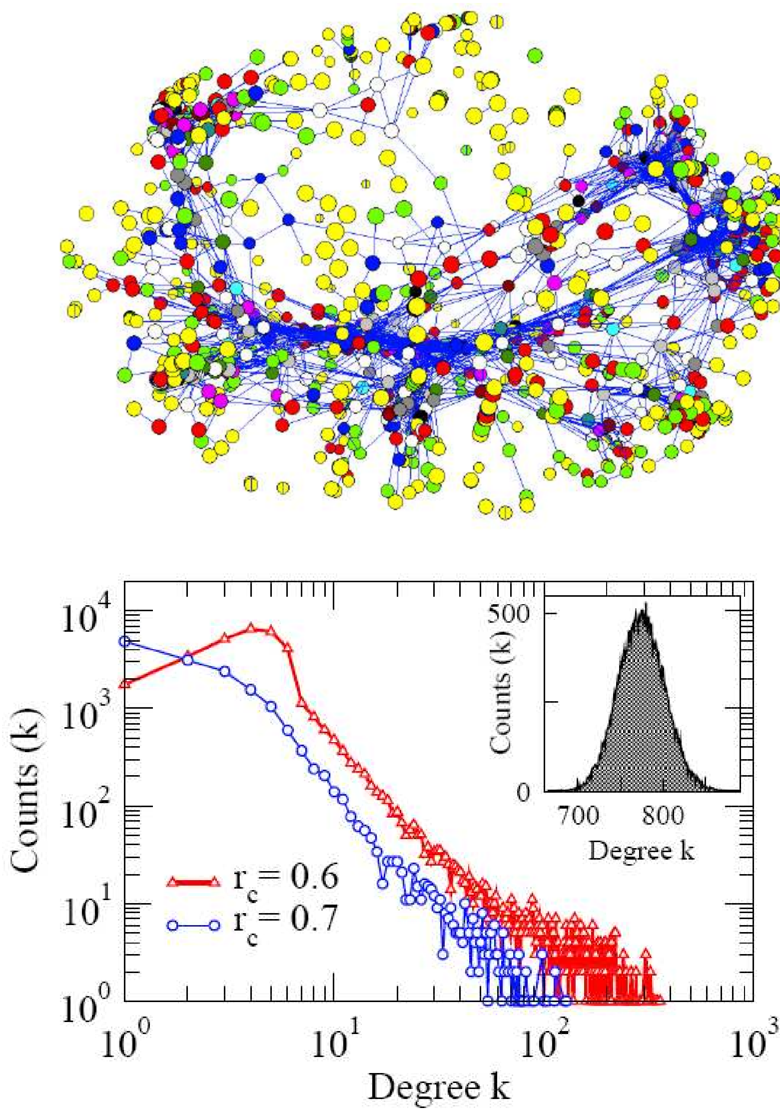

Fig. 5. A typical brain network extracted from functional magnetic resonance imaging. Top panel shows a pictorial representation of the network. The bottom panel shows the degree distribution for two correlation thresholds r_c. The inset depicts the degree distribution for an equivalent randomly connected network. Data re-plotted from [31].

6 Functional brain networks are complex

Functional magnetic resonance imaging (fMRI) allows to monitor non invasively spatio-temporal brain activity under various cognitive conditions. Recent work using this imaging technique demonstrated complex functional networks of correlated dynamics responding to the traffic between regions, during behavior or even at rest (see methods in [31]). The data is analyzed in the context of the current understanding of complex networks (for a review see [33]). During any given task the networks are constructed first by calculating linear correlations between the time

series of brain activity in each of $36 \times 64 \times 64$ brain sites. After that, links are said to exist between those brain sites whose temporal evolutions are correlated beyond a pre-established value r_c.

Figure 5, shows a typical brain functional network extracted with this technique. The top panel illustrates the interconnected network's nodes and the bottom panel shows the statistics of the number of links (i.e., the degree) per node. Note the high non-uniformity in the interaction between nodes. There is a few very well connected nodes in one extreme and a large number of nodes with a single connection. The typical degree distribution approaches a power law distribution with an exponent around 2. Other measures revealed that the number of links as a function of -physical- distance between brain sites also decays as a power law, something already confirmed by others [34] using different techniques. Two statistical properties of these networks, path length and clustering were computed as well. The path length (L) between two brain locations is the minimum number of links necessary to connect both sites. Clustering (C) is the fraction of connections between the topological neighbors of a site with respect to the maximum possible. Measurements of L and C were also made in a randomized version of the brain network. L remained relatively constant in both cases while C in the random case resulted much smaller, implying that brain networks are "small world" nets, a property with several implications in terms of cortical connectivity, as discussed further in [32,33]. In summary, the work in [31] showed that functional brain networks exhibit highly inhomogeneous scale free functional connectivity with small world properties. Although these results admit a few other interpretations, the long range correlations demonstrated in these experiments are consistent with the picture of the brain operating near a critical point. Recent work from Achard and colleagues [35] sheds light over these aspects. They analyze fMRI time series from 90 cortical and subcortical regions acquired from healthy volunteers in the resting state. Using similar methods they find similar small-world topology of sparse connections in the graphs of brain functional networks, most salient in the low-frequency range. They report an exponentially truncated power law for the degree distribution, and when the network was tested for damage, (by deleting nodes and recalculating topological measures) they found that it was "more resilient to targeted attack on its hubs than a comparable scale-free network, but about equally resilient to random error." Thus, they have not only confirmed and extended the initial observations of small world connectivity but also characterized further higher order topological features of the extracted networks. Most recently, Basset and colleagues [36,37] analyzed the topology and synchronizability of frequency-specific brain functional networks using wavelet decomposition of magnetoencephalographic time series recordings concluding that "human brain functional networks demonstrate a fractal small-world architecture that supports critical dynamics and task-related spatial reconfiguration while preserving global topological parameters". Stam and colleagues has been actively looking at functional brain networks defined from electroencephalogram. In the most recent work [38] they reported "loss of small-world network characteristics" in Alzheimer's disease patients. As more detailed knowledge of the properties

of healthy and abnormal brain functional networks is achieved, the need to integrate this data in a cohesive picture grows, as discussed recently by Sporns and colleagues [39].

7 Outlook

In these notes, we have attempted to -provocatively- inject some connections between ubiquitous dynamics of complex systems and brain cognition and behavior. In that spirit we also recognize that the most useful connections are also the most tenuous and hard to perceive at first. It is also probable that it is yet premature times for brain theory. We had already pictured brain theory at a stage comparable to physics in “pre-thermodynamic” times [40]. Imagine yourself in days previous to the notion of temperature. Similarities between scalding water and ice will be supported by their similar “burning” (to the touch) properties, when hot or cold were only subjective quantities. Of course, the notion of pressure and temperature together with the identification of phases changed everything. There is plenty of room for optimism that brain theory will eventually undergo similar transformation as Werner’s recent perspective [41] seems to convey.

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